

How Can Expertise be Defined? Implications of Research From Cognitive Psychology

Robert R. Hoffman
Adelphi University (now at the University of West Florida)

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INTRODUCTION

In Cognitive Psychology, the experimental study of expertise involves applying concepts and methods from a number of areas: problem solving, learning, and ergonomics, to name just a few. The study of expertise provides a focus for basic research on many phenomena of cognition, such as memory limitations and reasoning biases. It also provides a focus for discussion of issues in cognitive theory, such as those involving knowledge representation. The psychological study of expertise has been invigorated in recent years by the advent of expert systems, but studies of expertise can be found even in the earliest psychological research. Furthermore, a great deal of the research in the tradition of Judgment and Decision-making can be regarded, in hindsight, as studies of expertise (e.g., linear decision models of the reasoning of economists). Clearly, the literature of psychological studies of expertise is vast.

Space does not permit systematic summary and critique of every study. The more modest goals of this chapter are to: (1) illustrate the psychological/empirical approach and the research methods that have been used in the study of expertise, and (2) pull together some recent findings to see if progress can be made towards a general theory of expertise. Such a theory should explain developmental phenomena and expert-novice differences, and the relations of expertise to general intellectual functions. It should also entice us toward further research (Ericsson & Smith 1991).

In addition, the cognitive psychology of expertise should point to practical applications. By informing us about the nature of expertise at a cognitive level, psychological research has already had implications for the practice of knowledge

acquisition for expert systems (Cooke 1992; Hoffman 1987; Prietulla *et al.* 1989; Schumacher & Czerwinski 1992). This research has broader relevance to issues involving technology and technological change, including the problem of defining expertise and identifying experts, and training and skill acquisition. These broad issues are important for the advancement of our understanding of expert knowledge and the refinement of our technology for preserving and instilling expert knowledge in society at large (Klein 1992).

THE PROBLEM OF DEFINING EXPERTISE

Both psychological research on expertise and expert system development efforts have tended to define expertise rather loosely. In some cases, one can readily identify “The” experts, as in my own current research on expertise in meteorology involving the participation of researchers and forecasters at the U.S. National Atmospheric and Oceanographic Administration and National Weather Service (Hoffman 1991). How did I know my participants were experts? One was a forecaster for Shuttle launches and another was a designer of the first meteorological satellites. There could be little doubt of the expertise level of such individuals. In another study on military airlift scheduling (Hoffman 1987), there was only the one expert at a particular task!

In some domains there are “gold standards”—documentation which exhausts the domain knowledge—or senior experts who establish the standards and procedures that are used by the other practitioners in the domain. In some expert system projects, candidate experts have been selected on the basis of a simple subjective questionnaire about the candidate’s experience. In some domains, professional licensing has sufficed as a criterion for the identification of experts. Alternatively, a psychologist might rely on “advanced graduate students” in a particular domain. In a study on expertise in the classification of dinosaurs (Chi & Koeske 1983), the “experts” were children (ardent dinosaur hobbyists), yet their knowledge showed some of the features of expertise—depth of comprehension as evidenced in their differential classification of meat-eaters and plant-eaters.

In general, identifying experts has not been much of a problem in the practice of experimental psychology and in expert system development. (For detailed discussions, see Brulé & Blount 1989; Hart 1989; McGraw & Harbison-Briggs 1989; Prerau 1990.)

There are, however, situations in which there can be significant practical problems. For example, I was once consulted by the U.S. Government Accounting Office to deal with the problem of disagreement among expert toxicologists concerning decisions about the developmental toxicity and teratogenicity of chemical compounds. The issue involved social policy governing exposure and safety standards. If the “experts” are experts, why do they disagree? And since they do disagree, how can one rely on their judgments in setting policy?

The challenge to cognitive psychology is to generate an operational definition of expertise, one that focuses on cognitive factors, and that can be used operationally to identify experts. Expertise can be defined, at a cognitive level, in terms of (1) its development, (2) experts’ knowledge structures, and (3) experts’ reasoning processes.

Defining Expertise in Terms of Cognitive Development

In certain significant domains, such as air traffic control, training programs have a large “washout” rate—anywhere from 25%–75%, with 50% being typical. Practice does not always “make perfect” (Schneider 1985). The development of expertise, like all forms of development, is subject to individual differences in psychological and behavioral characteristics. However, developmentally speaking, expertise is not the same thing as intelligence. Traditional intelligence tests are intended to assess and predict performance in a particular context—schools. A given expert may possess low general intelligence or low ability outside their domain of expertise. Ceci and Liker (1986) examined the general intelligence of expert “handicappers”—people who are very good at predicting the final odds for horse races. In the experiment, the experts predicted the odds for a series of hypothetical horse races, derived from archived data so as to sample the ranges of the relevant variables such as horses’ speed and clearing prices. The results suggested that the reasoning of the handicappers is complex, but not correlated with general IQ—it taps skills that seem to be largely, if not entirely, different from the skills that standard intelligence tests measure.

The Developmental Progression

The development of expertise involves a progression from a superficial and literal understanding of problems (a qualitative mark of the cognition of novices) to an articulated, conceptual, and principled understanding (a qualitative mark of the cognition of experts). The accumulation of skill based on experience and practice are the key, not

maturational processes or time *per se*. Hence, two experts in a given domain can be of quite different ages, and it makes more sense to speak of developmental levels than stages.

The distinction between “novice” versus “expert” implies that development can involve both qualitative shifts and stabilizations in knowledge and performance. A number of phenomena suggest the occurrence of level-like qualitative shifts (Adelson 1984; Gaeth 1980; Phelps & Shanteau 1978; Spiro *et al.* 1989): (a) It is rare for a level to be skipped; (b) It is rare for someone to either regress or to fail to progress, unless they fall out of practice; (c) Expert teachers (or “masters”) can anticipate the errors a trainee will make depending on their skill level; (d) With practice, a skill loses the quality of being conscious, effortful, deliberate, and linear, and takes on the quality of automatic pattern recognition. In short, judgments become “intuitions” in that one can rapidly and effortlessly associate experiences, make decisions, or perform actions (more on this later). Such phenomena indicate that stage-like qualitative shifts are occurring as expertise develops.

In some domains, people who are regarded as “novices” can actually be very highly experienced. In the judging of livestock, one might remain a “novice” even after as much as ten years of experience at school and club training. Those who are regarded as “experts” have 20 to 30 years of experience. Workers in such domains naturally distinguish their peers who are good, even very good, from the “real” experts or what might be called the “grand masters” (Shanteau 1984, 1988, 1989). Clearly, the two terms “novice” and “expert” leave much to be specified. Additional distinctions on the continuum of development have been alluded to in the literature on expertise (*cf.* Foley & Hart 1992), and, as presented below, these can be expressed by the terminology of the “craft guilds” of the Middle Ages.¹

<i>Naivette:</i>	One who is totally ignorant of a domain.
<i>Novice:</i>	Literally, someone who is new—a probationary member. There has been some (“minimal”) exposure to the domain.
<i>Initiate:</i>	Literally, someone who has been through an initiation ceremony—a novice who has begun introductory instruction.
<i>Apprentice:</i>	Literally, one who is learning—a student undergoing a program of instruction beyond the introductory level. Traditionally, the apprentice is

¹ This scheme has been faulted for its reliance on an outdated, male-oriented perspective, and yet alternative terminological schemes have not been forthcoming. If one acknowledges that expertise develops, and that qualitative changes occur over the developmental period, then one must make some attempt at stage-like categorization, if only to motivate research. I would welcome alternative conceptual schemes and am myself not religiously attached to the diminutive “naivette” neologism.

immersed in the domain by living with and assisting someone at a higher level. The length of an apprenticeship depends on the domain, ranging from about one to 12 years in the craft guilds.

Journeyman: Literally, a person who can perform a day's labor unsupervised, although working under orders. An experienced and reliable worker, or one who has achieved a level of competence. It is possible to remain at this level for life.

Expert: The distinguished or brilliant journeyman, highly regarded by peers, whose judgments are uncommonly accurate and reliable, whose performance shows consummate skill and economy of effort, and who can deal effectively with certain types of rare or "tough" cases. Also, an expert is one who has special skills or knowledge derived from extensive experience with sub-domains.

Master: Traditionally, a master is any journeyman or expert who is also qualified to teach those at a lower level. Traditionally, a master is one of an elite group of experts whose judgments set the regulations, standards, or ideals. Also, a master can be that expert who is regarded by the other experts as being "the" expert, or the "real" expert, especially with regard to sub-domain knowledge.

These terms represent a first step toward a practical operational definition. Further specification of the cognitive functionality of experts comes from research on expert's knowledge and reasoning processes. What underlies the developmental milestones?

Defining Expertise in Terms of Knowledge Structure

In general, it does take a long time to become an expert, and by the time one has become an expert, one's knowledge is both specific to the domain and very extensive (Chase 1983; Chiesi *et al.* 1979; Glaser 1987; Scribner 1984). It has been shown empirically that experts draw more complex conceptual distinctions than novices. For experts, the level of "basic objects" within their domain of expertise is more highly differentiated (Murphy & Wright 1985). Estimates of the extent of expert knowledge put it anywhere from tens to hundreds of thousands of individual propositions, and somewhere in the neighborhood of 50,000 concepts (Lenat & Feigenbaum 1987; Simon & Gilmarin 1973). For example, chess masters can recognize tens of thousands of game patterns.

Knowledge Organization

Expert knowledge differs from novice knowledge in its organization as well as its extent. That is, concepts are interrelated in meaningful ways and memories are concept-, context-, and content-addressable (Chi *et al.* 1982; Glaser 1987; Lesgold 1984; Mandler 1967). Experts also rely on conceptual categories that are principled (or more "abstract") (Voss *et al.* 1983), and they know that conceptually different problem types may nonetheless manifest the same features (Murphy & Wright 1984).

Results from studies in which computer programmers comprehend and generate programs (while thinking aloud) have shown that experts represent programs in terms of the main processes that are needed to accomplish the goal of the program (Adelson 1981; Jeffries *et al.* 1981; McKeithen *et al.* 1981). Experienced programmers are better able to identify bugs, especially those that can be found only after a detailed conceptual understanding of program function. Expert programmers recall a much greater amount of a program than initiates, even after a short exposure, hypothetically because their memory organization falls at a more conceptual level.

Groen and Patel (1988) had expert medical diagnosticians and medical students read and recall descriptions of clinical cases. The results showed that experts tend to remember not the verbatim cases, but their underlying “gist” or meaning, including the expert’s own inferences. Of course, this finding has its analog in normal memory for short stories (Bartlett 1932). A number of recent studies of experts’ recall have shown this effect, and furthermore that experts in diverse domains are better able to reorganize and make sense of scrambled information (Chase & Simon 1973).

In a study of expert fighter pilots, Schvaneveldt *et al.* (1985) began by interviewing some experts to determine the basic elements involved in two particular scenarios, one simple and one complex. Example elements are “overtake,” “accelerate,” “the target is in range,” and “the target is maneuvering.” Next, some trainees and experts were presented with a list of the basic elements. Their task was to make pair-wise comparisons and rate the items’ similarity. For the experts, the concepts seemed to cluster into three groups: Concepts that refer to events, concepts that refer to distances, and concepts that refer to orientation. The scaling data were then transformed into a graphical representation of concept-nodes and relational links. The experts produced similar graphs, in which the important relations were made salient, while the initiates all produced different and less organized graphs.

Empirical studies of expert chemists, social policy makers, electronic circuit designers, clinical psychologists, nurses, mathematicians, radiologists, telephone system operators, and musicians have all produced similar demonstrations of the expert-novice difference in memory organization (for a full bibliography, see Hoffman 1992).

Some of the knowledge of experts is represented in the form of “mental models” which are dynamic, concept-based imaginal representations of entities, events, properties, and relations (Gentner & Gentner 1980; Larkin 1983; Schumacher & Czerwinski 1992). The transformations or changes within a mental model represent the cause-effect or

principled relations among the modeled objects or events. A striking example of this would be physicist Nikola Tesla's ability to imaginably design and test electric motors. (Reportedly, many engineers' develop an ability to imaginably design and test structures such as bridges.) Mental models resemble the modeled world perceptually—this is the imagery component. But they also represent abstract concepts and functional relations. There are some domains, such as government domestic policy-making, where mental models are largely “abstract” (Voss *et al.* 1983). That is, they take the form of schemata that capture the essential features—rather than the details and variabilities—of concepts, categories, or situations (Abelson 1981; Lesgold *et al.* 1983; Soloway *et al.* 1988).

Defining Expertise in Terms of Reasoning Processes

Although it is now fairly clear that expertise can be defined in terms of development and in terms of knowledge structure, it is less clear that expertise can be defined in terms of any special reasoning processes that experts might possess.

Experts are “Just Plain Folk”

Many of the reasoning strategies and sequences that have been observed in psychological research on problem solving have also been observed in the highly skilled reasoning of professional waitresses, inventory managers, and product assemblers, to name just three domains. In terms of the general or basic problem solving strategies such as “divide and conquer” and “means-end analysis,” experts seem to be “just plain folk.”

Duncker (1945) presented word problems and mathematics problems to college students and had them “think aloud” during their attempts to solve the problems. Duncker observed that there were two general kinds of strategy or search, which he referred to as “suggestion from below” and “suggestion from above.” In the modern literature on problem solving these two particular concepts are referred to as top-down and bottom-up search. According to Duncker's specification of reasoning, problem solving often involves a cycle:

- (1) Inspect available data---->
- (2) Form a mental model and related hypotheses---->
- (3) Seek information to test alternative hypotheses---->
- (4) Cycle back to Step 2; that is, refine the mental model---->
- (5) Produce a judgment.

A number of studies of expertise and knowledge acquisition have recently revealed the refinement cycle or some variation of it (e.g., Anderson 1982; Chi *et al.* 1982). The

cycle appeared explicitly in Lederberg and Feigenbaum's (1968) early description of the goal for their AI program DENDRAL, an expert system for the analysis of organic molecules: "Data somehow suggest an hypothesis, and deductive algorithms are applied to the hypothesis to make logically necessary predictions; these are then matched with the data in a search for contradictions" (p. 187).

Although expert and "everyday" reasoning may rely on the same fundamental cognitive operations, the flow of expert reasoning is definitely shaped by the tasks that are involved in the domain (Greeno 1978; Scribner 1984).

Expert Reasoning IS Special

Experts are very adept at their usual or familiar tasks (Hoffman *et al.* 1993). Hence, disruption of their familiar task can cause the expert's superior performance to decline markedly—in a disrupted task they cannot form meaningful representations or solutions. For example, chess masters' memory for game positions is disrupted for scrambled games (Chase & Simon 1973). Expert bridge players are disrupted by meaningful rule changes—who leads each round—more than by superficial changes—such as the names of the suits (Sternberg & Frensch 1992). Expert programmers' memory for programs is disrupted if the programs are scrambled (McKeithen *et al.* 1981).

Larkin (1983) asked physics students and experienced physicists to solve mechanics problems (involving levers, weights, inclined planes, pulleys, forces, etc.) while thinking aloud. The results of a number of such studies on physics problem solving have shown that experts and novices reason in different ways. That is, the basic reasoning operations or strategies are applied in different orders and with different emphases. In the initial stages of problem solving, experts spend proportionately more time than novices in forming a conceptual understanding of the problem. Furthermore, as I have pointed out, the experts generate representations that are conceptually richer and more organized than those of the novices. Novices tend to use hastily formed "concrete" (that is, superficial) problem representations whereas experts use "abstract" representations that rely on "deep knowledge"; that is, imaginal and conceptual understanding of functional relations and physical principles that relate concepts (in the case of the research on experts at mechanics, principles such as conservation of energy). Furthermore, experts are better able to gauge the difficulty of problems and know the conditions for the use of particular knowledge and procedures (for example, if there is acceleration, use Newton's second law) (Chi *et al.* 1982).

Perceptual Skill

The special reasoning processes of experts often manifest themselves as perceptual skill (Klein & Hoffman 1993; Lesgold *et al.* 1988). To illustrate: Upon witnessing the performance of a high diver, the expert sports commentator asserts that the diver's legs were not neatly tucked during a particular portion of the dive. Sure enough, the slow motion replay shows us novices that the expert was right. A more esoteric example is the sexing of newly hatched chicks, but examples can also be found in "ordinary" skills such as speech perception, face perception, and reading—which are actually remarkable accomplishments.

Myles-Worsley *et al.* (1988) had expert radiologists and medical students observe and then attempt to recognize a series of chest X-rays. Reaction time data showed that experts allocated their attention more efficiently, focusing on abnormal features that distinguished the images. Similarly, Norman *et al.* (1989) demonstrated the effect of perceptual learning in a study of student, intern, and resident dermatologists, in which the participants were shown 100 slides for diagnosis. The researchers measured reaction time and error rates in a subsequent recognition task. The reaction time data showed that experts engaged in a rapid perceptual process that does not rely on independent analyses of separate cues. In other words, reaction times and errors were not predictable on the basis of the simple presence or absence of isolated features that are typical of each diagnostic category (Kundel & Nodine 1978).

Research has shown that experts in domains as diverse as architecture, nursing, and electronic circuit design can indeed "see" things that novices cannot: When novice livestock judges confront the judgment task they can miss seeing important features of livestock that experts readily detect (Phelps & Shanteau 1978); the eye movements of radiologists while they scan X-ray films are quite different from those of novices—the experts can selectively search for abnormalities (Kundel & Nodine 1978); and expert cardiologists directly comprehend cardiovascular biomechanical events as perceived through a stethoscope (Jenkins 1985). In many domains of expert decision making, such as firefighting, power plant operation, jurisprudence, and design engineering, experts often make decisions through rapid recognition of causal factors and goals, rather than through any explicit process of generating and evaluating solutions (Klein & Hoffman 1992).

With experience and practice, new distinctive features are discovered, permitting the active, strategic search for critical information. One gains an ability to rapidly detect

and discriminate, but not isolated features or cues. Rather, one learns to attend to invariant patterns that were not previously noticed. Over the course of development, perceptual skills change, permitting the rapid search, discrimination, recognition and comprehension of complex informational patterns (Norman *et al.* 1989).

In addition to its special reliance on perceptual skill, the reasoning of experts is also special in that it often relies on “case-based” reasoning.

Case-based Reasoning

Experts often refer to illustrative or prototypical examples of past cases when asked to justify or explain their decisions or actions. They like to “tell stories” (Klein & Hoffman 1992). Sometimes it seems as if a great deal of an expert’s knowledge is remembered in the form of previously encountered cases. Hence, it has proved possible for developers of expert systems to elicit experts’ knowledge by presenting them with sets of specially prepared “test cases” (Hart 1989; McGraw & Harbison-Briggs 1989). Indeed, there are domains of expertise wherein the primary method of reasoning involves explicitly comparing each given case to past cases. A clear example comes from avionics engineering (Weitzenfeld 1989). The task of some avionics engineers is to predict the reliability and maintainability of new aircraft components or systems, and they do so on the basis of historical data about functionally or structurally similar components on older aircraft.

The reasoning of experts is also special in terms of its flexibility.

Reasoning Flexibility

As one expert soil judge pointed out when confronted with a classification error, “I helped set up the methods for classifying soils, and the methods may need to be changed for this type of case.” He then went on to suggest precisely how the new judgments might be made (cited in Shanteau 1989). The performance change which occurs over development includes an increased ability to form multiple alternative interpretations or representations of problems, and an increased ability to revise old strategies and create new ones as problem solving proceeds (Shanteau & Phelps 1977).

Reasoning flexibility is necessary in domains where some tasks are “ill-structured” (Ettenson *et al.* 1987; Reitman 1965; Simon 1973). (An example of the structure dimension would be: “Write a good essay” versus “Debug this electronic circuit.”) But experts in all domains appear to possess the ability to generate scenarios or frameworks for

reinterpreting novel difficult decisions. One might expect that wholesale delivery truck drivers, warehouse inventory managers, office clerks, and product assemblers would mostly rely on routine procedures and tasks, rather like the airline pilot's checklist. Scribner (1984, 1986) presented highly experienced workers with some test cases, and revealed a great deal of reasoning flexibility in service of efficiency and economy (see also Kusterer 1978; Schön 1983).

Shanteau and Phelps (1977) demonstrated that when unique situations are encountered, expert livestock judges were able to generate meaningful special-case strategies. In contrast, novices persisted in following the well-learned decision rules, even when they were inappropriate. A well-regarded livestock judge noted that one of the biggest difficulties in teaching students "is their persistence in using inflexible and outdated standards" (cited in Shanteau 1987). When confronted with an error, novices frequently appear more interested in rationalizing or defending their past decisions than in learning from them (Groen & Patel 1988).

The Declarative-to-Procedural Shift

One of the potential problems involved in identifying experts stems from the basic nature of knowledge and skill: Whenever a skill (e.g., reading, bicycle riding) is highly practiced, knowledge that is initially taught explicitly becomes tacit or "automatic" (Lesgold *et al.* 1988; Sanderson 1989). This leads to a potential paradox: As experts learn more, they lose awareness of what they know, and the knowledge they need to show in order to prove that they are experts (or in order to build an expert system) is the very knowledge the expert is least able to describe or talk about! Some developers of expert systems have observed that highly skilled experts can carry out tasks without being aware of how or why they do what they do (Kidd & Welbank 1984).

Broadbent and his colleagues (Berry 1987; Berry & Broadbent 1984; Broadbent & Aston 1978; Broadbent *et al.* 1986) have demonstrated that when learning to control a complex system (e.g., a simulated model for a transportation system or an economic system), an individual may achieve a high level of performance through lots of practice, yet be unable to correctly answer questions about the system that is being controlled. There can be an increase in task performance without an increase in verbalizable knowledge, or a drastic change in conceptual understanding and verbalizable knowledge without a corresponding major change in task performance.

Fortunately, the concept of “knowledge that is not verbalizable in principle” still appears to be hypothetical. Furthermore, the existence of “knowledge that is verbalizable only with some difficulty” has not presented an insurmountable obstacle to either the task of identifying experts or the task of developing expert systems. It is clear nevertheless that the process of identifying experts should never rely on a single method for eliciting knowledge or demonstrating that an individual possesses expertise (Hartley 1981). Different knowledge elicitation methods may yield different types or forms of knowledge, and special methods may be needed to elicit tacit or nonverbalizable knowledge (Cooke 1992). A number of developers of expert systems have claimed that special tasks are needed in order to reveal experts’ tacit or procedural knowledge, and their refined reasoning strategies (Hoffman *et al.* 1993).

IMPLICATIONS

I have used the problem of defining expertise to provide a conceptual organization for a discussion of recent psychological research on expertise. Along the way, I illustrated the sorts of research methods and hypotheses that have been explored. These also have implications for other issues addressed in this volume.

Implications for A Resolution of Divergent Perspectives

A given psychological experiment may seem irrelevant from some other discipline or paradigm, it may seem too narrow methodologically, or may seem tangential to the “real” issues. Experimental psychologists have their own purposes and methodological strictures, to be sure, However, I would argue that neither psychological research nor theory should be at odds with any other disciplinary perspective or empirical finding. Take, for example, the supposed contrast between the cognitive/psychological and sociological perspectives.

One question, salient in recent debates, is: “Where does expertise reside—in the heads of experts or in the total social situation encompassing them?” By my reading of the debate, psychologists and sociologists really agree more than they disagree, and can be accused of just beating each other’s straw men.

There are many metaphors for defining what is meant by “knowledge” (Regoczei & Hirst 1992), and one is not compelled to conceive of knowledge as a thing, in the first

place, nor restrict it to any either-or categorization. Knowledge—in a sense—must exist inside heads. Where else could it reside? As an analogy (from Ford 1993), when the expert carpenter leaves the workshop, something does leave with him. Could you or I use the tools to build, say, a china cabinet?

However, knowledge—in a sense—is an attribution that resides in social groups. How else could it be developed, taught, or standardized? How could someone be regarded as an expert if her judgments are not followed in the decisions made by other people? As we have pointed out, expertise clearly depends upon the domain or “context.” Just as being a plumber or a lawyer or a meteorologist requires knowing different things, relying on different skills, and being held more-or-less accountable to others or to professional standards, so will experts in these areas demonstrate various abilities in different ways. So too might there appear differences in the developmental progression as knowledge and skills are acquired and refined. In some domains, individuals are expected or required to reach a moderate level of proficiency—the journeyman level—whereas in other domains the experts are distinguished from journeymen only after decades of additional experience. In some domains—designing, accountancy—the experts do not always play an active role in carrying out their decisions, they basically provide information or advice to the decision-makers. In other domains—business management, nursing—the experts must make decisions and act upon them. In such domains, the ability to take direct action may count as much as the ability to generate sound judgments.

Clearly, the total enterprise of exploring expertise will have to tap into a variety of perspectives, methodologies, and research questions, as well as explore a great variety of domains.

Implications for Training

The development of expertise usually requires years of costly training and experience—in many domains we need more experts and in most domains we need ways of more efficiently instilling expertise.² The story is told that in the early days of World War II there emerged a dire need for operators of large industrial looms. The problem was that it took about seven years to train loom operators, since a critical aspect of loom operation is to deal with all the various kinds of breakdowns that could

² Only in the first wave of expert systems work was it implied that expert systems had the potential to replace experts. Common wisdom now is that expert systems are tools.

happen. The reason, it turned out, was that certain breakdowns only occurred on average once every seven years. The solution was to build a loom that could be deliberately made to breakdown in various ways. Operators were trained quickly, and we Americans had clothes during the War (Jenkins 1983).

This story gets at the heart of things. The real problem is not the “knowledge acquisition bottleneck” discovered in early expert system projects, but the “training bottleneck” of getting knowledge into novices. Psychological research suggests that the instillation of perceptual expertise might be facilitated by procedures which simulate familiar tasks (as in the loom story) and by procedures which expose trainees to test cases which sample the range of variability of the critical variables. Refined or specialized reasoning might be instilled by procedures which expose trainees to a variety of “tough” or atypical cases (Klein & Hoffman 1992).

Such recommendations for training are largely promissory. The psychological research may have yielded air-tight demonstrations that experts do differ from novices, and that experts know a lot, but such findings only go so far in helping in the design of actual training programs. Clearly, cognitive psychologists need to get closer to this problem through collaboration with educational psychologists (*cf.* Glaser 1987).

Work lies ahead for developers of expert systems as well. A “good” expert system should promote the dissemination of expertise by playing a role in the training process (see Footnote 2). To do this, systems will have to include mechanisms for learning and forming analogies. Also, systems will have to be able to explain their own reasoning. Typically, when an expert system is queried about the reasoning behind a particular conclusion, the system responds by displaying a list of the rules it stepped through. Since the rules are usually in cryptic code, the “explanations” are not very explanatory. A good explanation capability will itself depend on a capability to form a model of the user’s knowledge and skill level. The system should also include a knowledge of teaching and explanation strategies. In order to support both the explanation and user model capabilities, expert systems will have to be able to reason using conceptual or “deep” knowledge.³

The use of expert systems to compensate for human limitations has considerable potential, but more work is needed on how to best provide that compensation. Informed

³ Within the field of artificial intelligence there is some debate about whether such advanced capabilities would detract from system portability. Furthermore, and to be fair, “good” expert systems are not as brittle as I imply, and it is widely recognized that rule sequence print-outs are not very explanatory.

by the results of psychological research on questions of knowledge elicitation, knowledge representation, and reasoning, new expert systems technology holds promise in the preservation and dissemination of wisdom, for the greater benefit of society.

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